On Sampling from a Finite Set of Independent Random Variables

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0. Let $X_1, X_2, ..., X_N$ be a set of N independent random variables and let S_n be the sum of $n (\leq N)$ of them chosen at random. In this paper we will show that S_n is for large values of n and under certain mild conditions on the distributions of the X_k 's, approximately Gaussian, and we will give an estimate of the remainder term.

This general situation covers for example the case of two-stage sampling. Bikelis [1] has proved a result similar to the present one for simple random sampling, which, of course, can be regarded as a special case of two stage sampling. Bikelis uses an expression for the characteristic function of the sum S_n given by Erdös and Rényi [2], which, as far as I can see, can not be used in the present more general situation.

In the case n=N, the sum S_n simply is the sum of *n* independent random variables, and then the remainder term given here essentially coincides with the classical ones given by Esséen [3].

1. In order to define the sampling procedure exactly, we introduce a random indicator vector $\mathbf{I} = (I_1, I_2, ..., I_N)$, where $I_k = 0$ or 1, $1 \le k \le N$, such that S_n contains the term X_k if and only if $I_k = 1$. We now have $S_n = \sum_{k=1}^{N} I_k X_k$. I is assumed to be independent of the set $X_1, X_2, ..., X_N$, and for every ordered sequence $\mathbf{i} = (i_1, i_2, ..., i_N)$ of *n* ones and N - n zeros, we put $P(\mathbf{I} = \mathbf{i}) = 1 / {N \choose n}$. We have $EI_k = \frac{n}{N} = f =$ the sampling ratio, and $EI_k I_l = \frac{n}{N} \cdot \frac{n-1}{N-1}$ for $k \ne l$. We introduce the moments $EX_k = \mu_k$ and $EX_k^2 = \beta_k$ and then get

$$ES_{n} = \sum_{k=1}^{N} EI_{k} X_{k} = f \sum_{k=1}^{N} \mu_{k}$$
$$ES_{n}^{2} = \frac{n}{N} \sum_{k} \beta_{k} + \frac{n}{N} \frac{n-1}{N-1} \sum_{k \neq l} \mu_{k} \mu_{l}.$$

We will now assume that the scale is chosen so that

$$\sum_{k=1}^{N} \mu_k = 0, \qquad (1.1)$$

$$\frac{1}{N} \sum_{k=1}^{N} \beta_k = 1.$$
 (1.2)

We then get $ES_n = 0$ and

$$\operatorname{Var} S_n = n \left(1 - \frac{n-1}{N-1} \alpha^2 \right) \quad \text{where } \alpha^2 = \frac{1}{N} \sum_{k=1}^N \mu_k^2.$$

In the following sections we will prove that S_n/\sqrt{n} is approximately Gaussian with zero mean and variance $1 - f \alpha^2$, and also give an estimate of the remainder term.

2. In this section we will give an exact expression for the characteristic function $\overline{f_n}(t)$ of S_n/\sqrt{n} , which is suitable for estimations of the remainder term.

Let $f_k(t)$ be the characteristic function of X_k , k = 1, k, ..., N. Then

$$\bar{f_n}(t) = {\binom{N}{n}}^{-1} \sum \left(\prod_j f_j \left(\frac{t}{\sqrt{n}} \right) \right)$$

where the products are taken over *n* different indices *j*, and the sum is taken over all $\binom{N}{n}$ different combinations of those indices. We now multiply both sides with the same function $e^{t^2/2}$ and get

$$e^{t^{2}/2}\bar{f}_{n}(t) = {\binom{N}{n}}^{-1} \sum \left(\prod_{j} e^{t^{2}/2n} f_{j}\left(\frac{t}{\sqrt{n}}\right)\right).$$

Now, if g(z) is a function of a complex variable z, analytic in a neighbourhood of the origin, we will denote by $\{g(z)\}_n$ the coefficient of z^n in its MacLaurin series. We may thus write

$$e^{t^{2}/2} \bar{f}_{n}(t) = {\binom{N}{n}}^{-1} \left\{ \prod_{k=1}^{N} \left(1 + z \ e^{t^{2}/2n} f_{k}\left(\frac{t}{\sqrt{n}}\right) \right) \right\}_{n}.$$

Introducing the functions

$$b_k(t) = e^{t^2/2n} f_k\left(\frac{t}{\sqrt{n}}\right) - 1, \quad k = 1, 2, ..., N$$
 (2.1)

and

$$B_{j}(t) = \frac{(-1)^{j+1}}{j} \sum_{k=1}^{N} b_{k}^{j}(t), \quad j = 1, 2, ..., n$$
(2.2)

we then get

$$e^{t^{2}/2} \bar{f}_{n}(t) = {\binom{N}{n}}^{-1} \left\{ (1+z)^{N} \prod_{k=1}^{N} \left(1 + \frac{z}{1+z} b_{k}(t) \right) \right\}_{n}$$

= ${\binom{N}{n}}^{-1} \left\{ (1+z)^{N} \exp\left(\sum_{k=1}^{N} \log\left(1 + \frac{z}{1+z} b_{k}(t) \right) \right) \right\}_{n}$
= ${\binom{N}{n}}^{-1} \left\{ (1+z)^{N} \exp\left(\sum_{k=1}^{N} \sum_{j=1}^{\infty} \frac{(-1)^{j+1}}{j} \left(\frac{z}{1+z} \right)^{j} b_{k}^{j}(t) \right) \right\}_{n}$
= ${\binom{N}{n}}^{-1} \left\{ (1+z)^{N} \exp\left(\sum_{j=1}^{n} \left(\frac{z}{1+z} \right)^{j} B_{j}(t) \right) \right\}_{n}$

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where the summation over j has been restricted to $j \leq n$, since greater values of j do not contribute to the coefficient for z^n . By expanding the different exponential functions in separate power series of their arguments and multiplying all series together, we get $(B_i = B_j(t))$:

$$e^{t^{2}/2} \bar{f}_{n}(t) = {\binom{N}{n}}^{-1} \left\{ (1+z)^{N} \sum \left(\frac{z}{1+z}\right)^{i_{1}} \frac{B_{1}^{i_{1}}}{i_{1}!} \left(\frac{z}{1+z}\right)^{2i_{2}} \frac{B_{2}^{i_{2}}}{i_{2}!} \cdots \left(\frac{z}{1+z}\right)^{ni_{n}} \frac{B_{n}^{i_{n}}}{i_{n}!} \right\}_{n}$$

$$= {\binom{N}{n}}^{-1} \sum \frac{B_{1}^{i_{1}} B_{2}^{i_{2}} \dots B_{n}^{i_{n}}}{i_{1}! i_{2}! \dots i_{n}!} \{z^{i_{1}+2i_{2}+\dots+ni_{n}}(1+z)^{N-i_{1}-2i_{2}-\dots-ni_{n}}\}_{n}$$

$$= {\binom{N}{n}}^{-1} \sum \frac{B_{1}^{i_{1}} B_{2}^{i_{2}} \dots B_{n}^{i_{n}}}{i_{1}! i_{2}! \dots i_{n}!} \binom{N-i_{1}-2i_{2}-\dots-ni_{n}}{n-i_{1}-2i_{2}-\dots-ni_{n}}$$

where the summations are taken over all combinations of integers $i_j \ge 0, 1 \le j \le n$, satisfying $i_1 + 2i_2 + \dots + n i_n \le n$.

We will now examine the binomial coefficients. Putting $\sum_{i=1}^{n} j i_i = p$, we have

$$\binom{N}{n}^{-1}\binom{N-p}{n-p} = \left(\frac{n}{N}\right)^p C_{N,n,p}$$
(2.3)

where

$$C_{N,n,p} = \frac{\left(1 - \frac{1}{n}\right) \cdots \left(1 - \frac{p - 1}{n}\right)}{\left(1 - \frac{1}{N}\right) \cdots \left(1 - \frac{p - 1}{N}\right)}.$$
(2.4)

If we define $C_{N,n,p}=0$ when p>n, we obtain the following final expression

$$e^{t^{2}/2} \bar{f}_{n}(t) = \sum_{\substack{i_{j} \ge 0\\ 1 \le j \le n}} \frac{(f B_{1})^{i_{1}} (f^{2} B_{2})^{i_{2}} \dots (f^{n} B_{n})^{i_{n}}}{i_{1}! i_{2}! \dots i_{n}!} C_{N, n, \sum_{j=1}^{n} j i_{j}}.$$
 (2.5)

In the following section we shall expand the functions $B_j(t)$ in power series of t. These series will reveal that for large values of n, $f^j B_j(t)$ is small for $j \neq 2$ but $f^2 B_2(t) \approx f \alpha^2 t^2/2$. These facts, together with the fact that $C_{N,n,p} \approx 1$ when n is large, will give that

$$e^{t^{2}/2} \tilde{f}_{n}(t) \approx \sum \frac{(f^{2} B_{2})^{i_{2}}}{i_{2}!} \approx e^{f \alpha^{2} t^{2}/2}.$$

3. We now assume that all moments of the third order are finite, and put $E|X_k|^3 = \gamma_k$ and $\max_{1 \le k \le N} \gamma_k = \gamma$. We will denote by θ unspecified functions satisfying $|\theta| \le 1$, and assume that t satisfies

$$0 \leq t \leq \frac{1 - f \,\alpha^2}{10\gamma} \sqrt{n}.\tag{3.1}$$

From the general inequalities for moments, we get

$$|\mu_k| \leq \beta_k^{\frac{1}{2}} \leq \gamma_k^{\frac{1}{3}}$$

and thus

$$\frac{1}{N}\sum_{k=1}^{N}\mu_{k}^{2} \leq \frac{1}{N}\sum_{k=1}^{N}\beta_{k} \leq \frac{1}{N}\sum_{k=1}^{N}\gamma_{k}^{\frac{2}{3}} \leq \gamma^{\frac{2}{3}}$$

which gives $\alpha^2 \leq 1 \leq \gamma$.

Thus (3.1) implies $0 \le t/\sqrt{n} \le 0.1$. We now get

$$e^{t^2/2n} = 1 + \frac{t^2}{2n} + 0.51\theta \left(\frac{t^2}{2n}\right)^2 = 1 + \frac{t^2}{2n} + \frac{\theta t^3}{70n\sqrt{n}}$$

and from (2.1)

$$b_k(t) = \left(1 + \frac{t^2}{2n} + \frac{\theta t^3}{70n\sqrt{n}}\right) f_k\left(\frac{t}{\sqrt{n}}\right) - 1$$
$$= f_k\left(\frac{t}{\sqrt{n}}\right) - 1 + \frac{t^2}{2n} f_k\left(\frac{t}{\sqrt{n}}\right) + \frac{\theta t^3}{70n\sqrt{n}}.$$

By using the usual Taylor expansion for a characteristic function,

$$f_k(t) = 1 + i t \mu_k - \frac{t^2}{2} \beta_k + \frac{\theta}{6} t^3 \gamma_k$$

we get

$$b_{k}(t) = \frac{it\,\mu_{k}}{\sqrt{n}} + \frac{(1-\beta_{k})\,t^{2}}{2\,n} + 0.7\,\theta\frac{\gamma\,t^{3}}{n\,\sqrt{n}}.$$
(3.2)

Introducing the inequality (3.1) in the last terms, we also have

$$b_{k}(t) = \frac{it\,\mu_{k}}{\sqrt{n}} + 0.57\,\theta\,\frac{t^{2}}{n}\,\gamma^{\frac{2}{3}}$$
(3.3)

and

$$b_k(t) = 1.1 \theta \frac{\gamma^{\frac{1}{5}} t}{\sqrt{n}}.$$
 (3.4)

From (3.3) we get

$$b_k^2(t) = -\frac{\mu_k^2 t^2}{n} + 1.2 \theta \frac{t^3 \gamma}{n \sqrt{n}}.$$
(3.5)

We will now use these expressions and (2.2) to estimate $f^{j}B_{j}(t)$. From (3.2) we get, taking into account that $\sum_{k=1}^{N} \mu_{k} = \sum_{k=1}^{N} (1 - \beta_{k}) = 0$

$$f B_1(t) = 0.7 \theta \frac{\gamma t^3}{\sqrt{n}} \tag{3.6}$$

from (3.5) we get

$$f^{2}B_{2}(t) = \frac{f\alpha^{2}t^{2}}{2} + 0.6\theta f \frac{\gamma t^{3}}{\sqrt{n}}$$
(3.7)

and from (3.4)

$$f^{j}B_{j}(t) = N\theta \left(1.1f \frac{\gamma^{3} t}{\sqrt{n}}\right)^{j}, \quad j = 1, 2, \dots.$$
 (3.8)

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We now arrive at three expressions, which we will use in the next section: (3.6) and (3.8) give

$$f B_1 + \sum_{j=3}^n f^j B_j(t) = 2.2 \theta \frac{\gamma t^3}{\sqrt{n}}$$
(3.9)

(3.7) and (3.1) give

$$f^{2} B_{2}(t) = f \alpha^{2} t^{2}/2 + 0.06 \theta t^{2} (1 - f \alpha^{2}) = 0.6 \theta t^{2} = 0.06 \theta t \sqrt{n}$$
(3.10)

and (3.1) and (3.10) give

$$\sum_{j=1}^{n} f^{j} B_{j}(t) = f \alpha^{2} t^{2}/2 + 0.28 \theta t^{2} (1 - f \alpha^{2}).$$
(3.11)

We also must examine the difference between $C_{N,n,p}$ and 1. From (2.4) it at once follows $0 \le C_{N,n,p} \le 1$. It is also immediately clear that

$$C_{N,n,p} \ge \left(1-\frac{1}{n}\right) \dots \left(1-\frac{p-1}{n}\right).$$

Now, $1-x \ge \exp(-2x)$ for $0 \le x \le \frac{1}{2}$, so when $p \le n/2$, we have

$$C_{N,n,p} \ge \exp\left(-2\left(\frac{1}{n} + \dots + \frac{p-1}{n}\right)\right) = \exp\left(-p(p-1)/n\right) \ge 1 - p(p-1)/n \ge 1 - p^2/n.$$

But this inequality is always true for $p \ge n/2$ if $n \ge 4$, which we will always assume, and thus for all p:

$$1 - \frac{p^2}{n} \le C_{N, n, p} \le 1.$$
 (3.12)

4. We now return to (2.5) and divide the sum \sum of the right side into two parts $\sum = \sum_{1} + \sum_{2}$, where \sum_{1} is the sum of all terms with $i_{1} = i_{3} = i_{4} = \cdots = i_{n} = 0$ and \sum_{2} is the rest. Let $C_{i}(t)$ be functions, obtained in the preceeding section, satisfying $|f^{j}B_{j}(t)| \leq C_{j}(t)$. We can then majorize $|\sum_{2}|$ by replacing every $f^{j}B_{j}(t)$ by $C_{j}(t)$ and $C_{N,n,p}$ by 1. We then obtain $(C_{j} = C_{j}(t))$:

$$\left|\sum_{2}\right| \leq \exp(C_{1} + C_{2} + \dots + C_{n}) - e^{C_{2}} = e^{C_{2}} \left(\exp(C_{1} + C_{3} + \dots + C_{n}) - 1\right)$$

By using the elementary inequality

$$|e^{x} - 1| \le |x| |e^{|x|} \tag{4.1}$$

we get $|\sum_2| \leq (C_1 + C_3 + \dots + C_n) \exp(C_1 + C_2 + C_3 + \dots + C_n)$. (3.9) and (3.11) now give

$$\left|\sum_{2}\right| \leq \frac{2.2\gamma t^{3}}{\sqrt{n}} \exp\left(f \,\alpha^{2} \, t^{2} / 2 + 0.28 \, t^{2} \left(1 - f \,\alpha^{2}\right)\right)$$

that is

$$|\exp(-t^2/2)\sum_2| \leq \frac{2.2\gamma t^3}{\sqrt{n}} \exp(-0.22 t^2 (1-f\alpha^2)).$$
 (4.2)

We will now estimate \sum_{i} . By definition

$$\sum_{1} = \sum_{i=0}^{\infty} \frac{(f^2 B_2)^i}{i!} C_{N, n, 2i} = \exp(f^2 B_2) - \sum_{i=0}^{\infty} \frac{(f^2 B_2)^i}{i!} (1 - C_{N, n, 2i}).$$
(4.3)

From (3.7), (4.1) and (3.10) we immediately get

$$|\exp(f^2 B_2) - \exp(f \alpha^2 t^2/2)| \le 0.6 f \frac{\gamma t^3}{n} \exp(f \alpha^2 t^2/2 + 0.06 t^2 (1 - f \alpha^2))$$

that is

$$\left|\exp\left(-t^{2}/2+f^{2}B_{2}\right)-\exp\left((1-f\alpha^{2})t^{2}/2\right)\right| \leq 0.6f\frac{\gamma t^{3}}{\sqrt{n}}\exp\left(-0.44t^{2}(1-f\alpha^{2})\right).$$
 (4.4)

By using (3.12) we obtain for the last sum \sum_{3} in (4.3):

$$\left|\sum_{3}\right| \leq \sum_{i=0}^{\infty} \frac{C_{2}^{i}}{i!} \cdot \frac{(2i)^{2}}{n} = \frac{4}{n} C_{2}(1+C_{2}) e^{C_{2}}$$

and from (3.10)

$$|\exp(-t^2/2)\sum_3| \leq 0.24 \frac{t(1+t^2)}{\sqrt{n}} \exp(-0.44(1-f\,\alpha^2)\,t^2).$$
 (4.5)

Combining the expressions (4.2), (4.4) and (4.5), we now obtain

$$\left| \tilde{f}_{n}(t) - \exp\left(-(1 - f \,\alpha^{2}) \, t^{2} / 2 \right) \right| \leq 3.1 \, \frac{\gamma(t + t^{3})}{\sqrt{n}} \exp\left(-0.22 \, (1 - f \,\alpha^{2}) \right)$$
(4.6)

for $0 \leq t \leq \frac{(1-f\alpha^2)\sqrt{n}}{10\gamma}$.

By using (4.6) in Esséens inequality (Feller [4], p. 533)

$$|F(x) - G(x)| \leq \frac{2}{\pi} \int_{0}^{T} \left| \frac{f(t) - g(t)}{t} \right| dt + \frac{24}{\pi T} \sup_{x} |G'(x)|.$$
(4.7)

We now easily arrive in the following theorem, which is the main result of this paper.

Theorem. Let $X_1, X_2, ..., X_N$ be independent random variables and let S_n be the sum of n of them chosen at random. If $EX_k = \mu_k$, $EX_k^2 = \beta_k$, $E|X_k|^3 = \gamma_k$, where $\sum_{k=1}^N \mu_k = 0$, $\frac{1}{N} \sum_{k=1}^N \beta_k = 1$, $\alpha^2 = \frac{1}{N} \sum_{k=1}^N \mu_k^2$ and $\gamma = \max_{1 \le k \le N} \gamma_k$, then $\left| P\left(\frac{S_n}{\sqrt{n(1-f\alpha^2)^3}} \le x\right) - \Phi(x) \right| \le \frac{60\gamma}{\sqrt{n(1-f\alpha^2)^3}}$

where $\Phi(x) = (2\pi)^{-\frac{1}{2}} \int_{-\infty}^{x} \exp(-y^{\frac{2}{3}}) dy$ is the normalized Gaussian distribution function and $f = \frac{n}{N}$.

Remark 1. The constant 60 is by no means the smallest one which satisfies this inequality. The value is a consequent of the way these calculations have been made and especially of the number 10 chosen in (3.1).

Remark 2. If n=N, S_n is the sum of N independent random variables. If in this case the variables have the same distribution, the remainder term in Theorem agrees with the one obtained by Esséen [3] (cf. Feller [4], p. 542).

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Remark 3. If the set of variables $(X_1, X_2, ..., X_N)$ does not satisfy the normalizing conditions (1.1) and (1.2), we can easily obtain a new set $(X'_1, X'_2, ..., X'_N)$ which does satisfy (1.1) and (1.2), by a linear transformation. Application of the result of the theorem to this new set of variables gives, in terms of the original variables

$$\left| P\left(\frac{S_n - n\mu}{\sqrt{n\left[\frac{1}{N}\sum_{k=1}^N \sigma_k^2 + \frac{1 - f}{N}\sum_{k=1}^N (\mu_k - \mu)^2\right]}} \le x\right) - \Phi(x) \right|$$
$$\le \frac{60}{\sqrt{n}} \frac{\max_{1 \le k \le N} E |X_k - \mu|^3}{\left[\frac{1}{N}\sum_k \sigma_k^2 + \frac{1 - f}{N}\sum_k (\mu_k - \mu)^2\right]^{\frac{3}{2}}}$$
$$EX_k, \ \mu = \frac{1}{N} \sum_{k=1}^N \mu_k \text{ and } \sigma_k^2 = \operatorname{Var} X_k.$$

where μ_k = EX_k, μ = - N ∑_{k=1} μ_k and σ_k² = Var X_k.
 5. We will now indicate how this theoretical result may be used when estima-

ting the mean μ of a finite universe by two-stage sampling. Let the universe consist of N primary units P_1, P_2, \ldots, P_N , each of which consists of M_1, M_2, \ldots, M_N secondary units respectively. Every secondary unit in P_k is characterized by a real number a_{kj} , $1 \le j \le M_k$, $1 \le k \le N$. The object of the statistical experiment is to estimate the mean

$$\mu = \frac{1}{M} \sum_{k=1}^{N} \sum_{j=1}^{M_k} a_{kj}, \text{ where } M = \sum_{k=1}^{N} M_k$$

is the total number of secondary units in the universe.

Let now Z_k be the sum of the numbers a_{kj} obtained by a random selection of n_k secondary units out of P_k , $1 \le k \le N$. If $m_k = \frac{1}{M_k} \sum_{j=1}^{M_k} a_{kj}$ is the mean and $s_k^2 = \frac{1}{M_k - 1} \sum_{j=1}^{M_k} (a_{kj} - m_k)^2$ is the variance of P_k then $EZ_k = n_k m_k$ and $Var Z_k = \frac{n_k (M_k - n_k)}{M_k} s_k^2$.

We now put $X_k = \frac{N}{M} \frac{M_k}{n_k} Z_k$ and apply the Theorem to the set $(X_1, X_2, ..., X_N)$. We have $\mu_k = EX_k = \frac{N}{M} M_k m_k$ and $\sigma_k^2 = \text{Var } X_k = \frac{N^2}{M^2} \frac{M_k (M_k - n_k)}{n_k} s_k^2$. If S_n is the sum of $n X_k$'s chosen at random, then $ES_n = \frac{n}{N} \sum EX_k = n\mu$, so $\mu^* = \frac{S_n}{n}$ is an unbiased estimate of μ , which, according to our theorem, is approximatively Gaussian with mean μ and variance

$$\frac{1}{nN} \left[\sum_{k=1}^{N} \frac{N^2}{M^2} \frac{M_k - n_k}{n_k} s_k^2 + (1 - f) \sum_{k=1}^{N} \left(\frac{NM_k m_k}{M} - \mu \right)^2 \right].$$

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